

# Pearson's Correlation Coefficient

between

X and Y  
for sample size n

definition

Hypotheses testing

$$-1 \leq r = \frac{S_{XY}}{\sqrt{S_{XX}} \sqrt{S_{YY}}} \leq 1$$

Where

$$S_{XY} = \sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})$$

$$= \sum_{i=1}^n X_i Y_i - n \bar{X} \bar{Y}$$

$$S_{XX} = \sum_{i=1}^n (X_i - \bar{X})^2$$

$$= \sum_{i=1}^n X_i^2 - n(\bar{X})^2$$

$$S_{YY} = \sum_{i=1}^n (Y_i - \bar{Y})^2$$

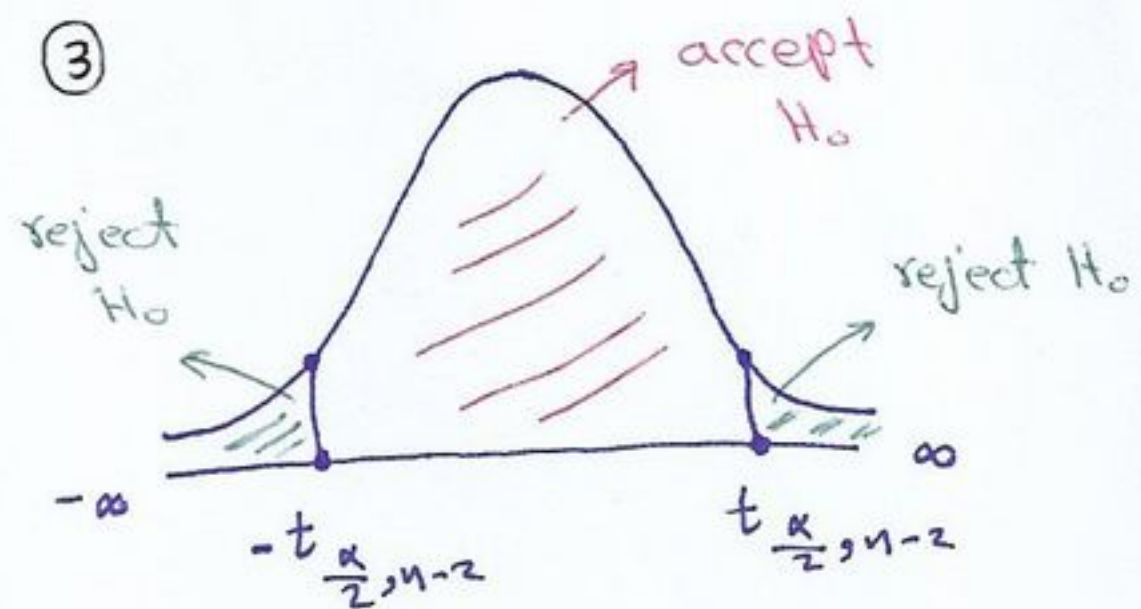
$$= \sum_{i=1}^n Y_i^2 - n(\bar{Y})^2$$

①  $H_0: \rho = 0$  vs  $H_1: \rho \neq 0$

② test statistics

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \sim t_{v=n-2}$$

③



④ We reject  $H_0$  if:

$$t_{T.S.} < -t_{\frac{\alpha}{2}, n-2}$$

or

$$t_{T.S.} > t_{\frac{\alpha}{2}, n-2}$$

otherwise, we will accept  $H_0$

We reject  $H_0$  if:

$$P\text{-value} \leq \alpha$$

where

$$P\text{-value} = 2P(T > |t_{T.S.}|)$$





## Some notes:

① Pearson's correlation coefficient  
for study  
the straight line/linear relationship  
between  
X and Y

②  $\rho$   $\rightarrow$  correlat. for population  
 $r$   $\rightarrow$  correlation for sample

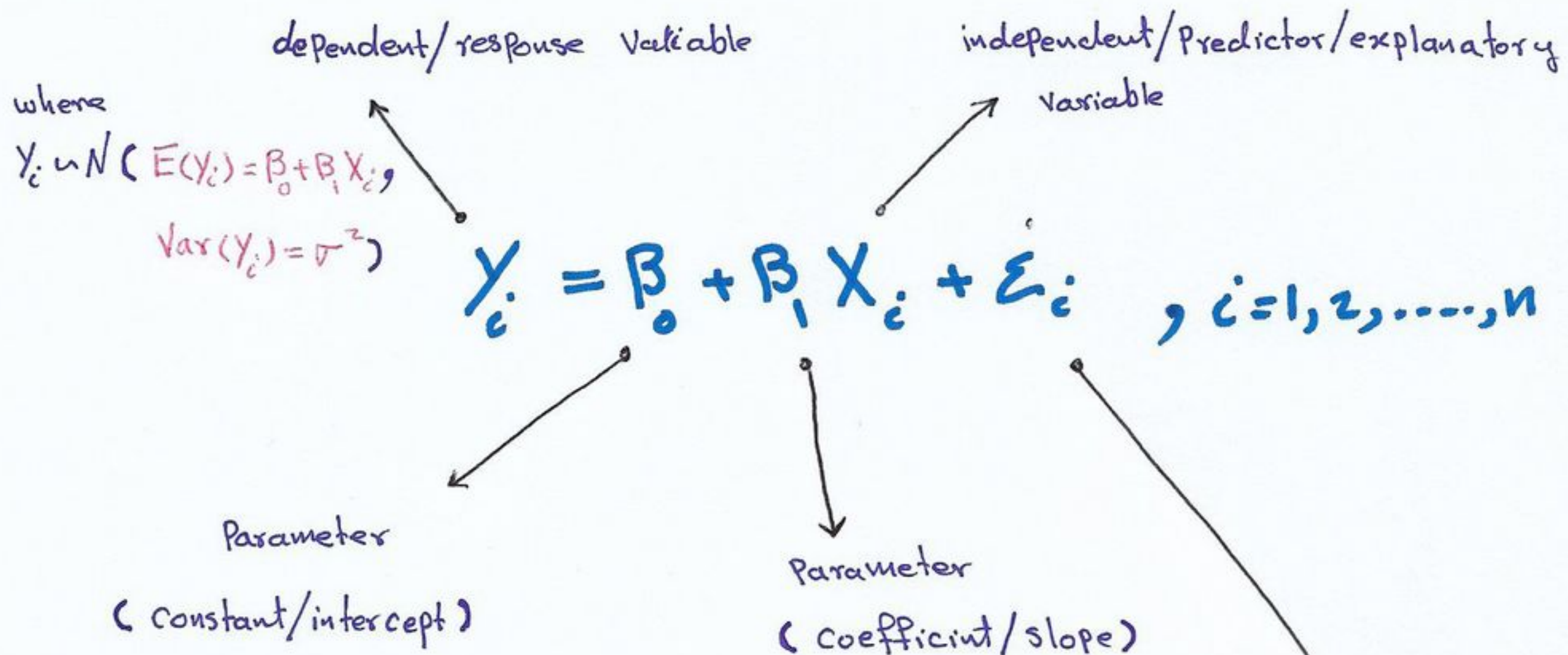
③ (i) Sign of  $r$

- $+$   $\rightarrow$  Positive direction/correlation i.e.  
increase-decrease X  $\leftrightarrow$  increase-decrease Y
- $-$   $\rightarrow$  negative direction/correlation i.e.  
increase-decrease X  $\leftrightarrow$  decrease-increase Y

(ii) Value of  $r$

- $|r|=0$   $\rightarrow$  no correlation/no linear relationship
- $0 < |r| \leq .25$   $\rightarrow$  weak
- $.25 < |r| < .75$   $\rightarrow$  moderate
- $.75 \leq |r|$   $\rightarrow$  strong

# Simple linear regression



$$\varepsilon_i \sim N(E(\varepsilon_i) = 0, \text{Var}(\varepsilon_i) = \sigma^2)$$

and

$$\text{Cov}(\varepsilon_i, \varepsilon_j) = 0, \quad \forall i \neq j$$





" Fitted regression line/equation "

or

" Prediction equation "

Fitted Value

$$\hat{y}_i = b_0 + b_1 X_i$$

independent/predictor variable

constant/intercept

coefficient/slope

$$\textcircled{1} b_0 = \begin{cases} \bar{y} - b_1 \bar{x} \\ \sum_{i=1}^n L_i y_i ; L_i = \frac{1}{n} - \frac{(X_i - \bar{X})}{S_{XX}} \end{cases}$$

$$\textcircled{1} b_1 = \begin{cases} \frac{S_{XY}}{S_{XX}} = r \sqrt{\frac{S_{YY}}{S_{XX}}} \\ \sum_{i=1}^n K_i y_i ; K_i = \frac{(X_i - \bar{X})}{S_{XX}} \end{cases}$$

$\textcircled{2} E(b_0) = \beta_0$  i.e.  $b_0$  is unbiased estimate of  $\beta_0$  ;

$$\text{Var}(b_0) = \text{MSE} \left( \frac{1}{n} + \frac{(\bar{X})^2}{S_{XX}} \right) ;$$

$$\text{standard error of } b_0 \text{ is } \text{S.E.}(b_0) = \sqrt{\text{Var}(b_0)}$$

$\textcircled{2} E(b_1) = \beta_1$  i.e.  $b_1$  is unbiased estimate of  $\beta_1$  ;

$$\text{Var}(b_1) = \frac{\text{MSE}}{S_{XX}} ;$$

$$\text{standard error of } b_1 \text{ is } \text{S.E.}(b_1) = \sqrt{\text{Var}(b_1)}$$

$\textcircled{3}$  The sampling distribution of  $b_0$  :

$$T_0 = \frac{b_0 - \beta_0}{\text{S.E.}(b_0)} \sim t_{n-2}$$

$\textcircled{3}$  The sampling distribution of  $b_1$  :

$$T_1 = \frac{b_1 - \beta_1}{\text{S.E.}(b_1)} \sim t_{n-2}$$

$\textcircled{4}$   $100(1-\alpha)\%$  confidence interval of  $\beta_0$  :

$$\beta_0 \in b_0 \pm t_{\frac{\alpha}{2}, n-2} \text{ S.E.}(b_0)$$

$\textcircled{4}$   $100(1-\alpha)\%$  confidence interval of  $\beta_1$  :

$$\beta_1 \in b_1 \pm t_{\frac{\alpha}{2}, n-2} \text{ S.E.}(b_1)$$

$\textcircled{*}$   $b_0$  and  $b_1$  are estimate of  $\beta_0$  and  $\beta_1$  , respectively ,

by

using

the least squares method / minimization procedure





## Some notes:

① The error/residual  $e_i = y_i - \hat{y}_i$ , then:

(i) sum of squared error:

$$SSE = \sum_{i=1}^n e_i^2$$

(ii)  $\sum_{i=1}^n e_i = 0$

(iii) mean squared error:

$$MSE = \hat{\sigma}^2 = s^2 = \frac{SSE}{n-2};$$

and  $E(s^2) = \sigma^2$  i.e.  $s^2$  is unbiased estimate of  $\sigma^2$

②  $\sum_{i=1}^n y_i = \sum_{i=1}^n \hat{y}_i$

③ The sum of weighted residuals:

(i) by  $X$ :  $\sum_{i=1}^n X_i e_i = 0$

(ii) by  $Y$ :  $\sum_{i=1}^n Y_i e_i = 0$

④ regression line through  $(\bar{X}, \bar{Y})$

⑤ for  $k_i$ : (i)  $\sum_{i=1}^n k_i = 0$

(ii)  $\sum_{i=1}^n k_i X_i = 1$

(iii)  $\sum_{i=1}^n k_i^2 = \frac{1}{S_{XX}}$

for  $L_i$ : (i)  $\sum_{i=1}^n L_i = 1$

(ii)  $\sum_{i=1}^n L_i X_i = 0$

(iii)  $\sum_{i=1}^n L_i^2 = \frac{1}{n} - \frac{(\bar{X})^2}{S_{XX}}$

⑥  $(SST_{OT} = S_{YY}) = SSE + SSR$   
total sum of squared error  $\swarrow$   $\searrow$  sum of squared regression  
 $= \sum_{i=1}^n (\hat{y}_i - \bar{Y})^2$

⑦ The coefficient of determination

$$0 \leq R^2 = \frac{SSR}{SST_{OT}} = 1 - \frac{SSE}{SST_{OT}} \leq 1$$

where:

(i)  $100R^2\%$  of total variation in  $Y$  is due to  $X$ .

(or)  $\swarrow$  (the least squares regression/regression line) explains  $100R^2\%$  of the variation in  $Y$ .

(ii) The simple correlation coefficient  $r = \sqrt{R^2}$  and the sign of it will taken from  $b_1$ .